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Research on Application of Artificial Neural Network in Fault Diagnosis of Chemical Process

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

Chemical processes are usually toxic, corrosive, flammable and explosive. If the process fails, the danger is extremely high. Traditional model-based fault diagnosis methods need to establish an accurate mathematical model of the system, while modern engineering processes are usually large in scale and complex, and it is difficult to establish an accurate mathematical model. Artificial neural network has been widely used in chemical process because of its advantages of parallel processing, self-adaptation, robustness, learnability and fault tolerance. Artificial neural networks based on "deep learning" have been successfully applied to fault diagnosis in various chemical processes. This article summarizes the principle and development process of artificial neural networks, and analyzes the research progress and application status of deep neural networks in chemical process fault diagnosis based on cases. Finally, it is pointed out that deep neural network in the field of chemical process fault diagnosis is of great significance in solving the impact of less fault data and system state changes on the fault detection rate, and promoting the industrial application of fault diagnosis models.

Keywords: Neural network; chemical process; fault diagnosis; deep learning.

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1. INTRODUCTION

In recent years, with the industrial upgrading, artificial intelligence is in the ascendant. As an important part of artificial intelligence, artificial neural network has attracted more and more people's interest. Chemical production has both continuous processes and many intermittent or semi-continuous processes with diversity. With the progress of modern chemical industry, large-scale, integration and automation have become the development direction. People put forward higher requirements for the performance of chemical production processes, hoping to optimize process operations to reduce equipment costs and energy consumption. Complex coupling characteristics of chemical production process make chemical intelligence inevitable The emergence of ANN makes up for the deficiency of traditional production technology. ANN is a nonlinear and adaptive information processing system composed of a large number of processing units interconnected It has significant advantages such as parallel processing, distributed storage and fault tolerance, self-learning, self-organization and self-adaptation, so it also has basic functions such as associative memory, non-linear mapping, classification recognition, and optimization calculations Therefore, ANN has been widely used in various complex scenarios. The main application areas include power generation or power demand forecasting [6-8], signal processing [9-11], TCM Symptom Diagnosis [12-14], intelligent driving [15-17], process control and Optimization[18-21], image processing [22-24], disease screening [25, 26], Cybersecurity [27], and etc. ANN also provides a new method for online control problems that are difficult to solve by traditional technologies in the chemical industry [28].

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2. ARTIFICIAL NEURAL NETWORK AND THE FUNDAMENTAL PRINCIPLE

Artificial neural network was originally developed based on biological principles. With the deepening understanding of human brain structure and stimulus response mechanism, people tried to simulate the mechanism of nervous system in dealing with complex information to establish a mathematical model, resulting in the initial artificial neural network. The typical structure of the neural network model can be illustrated by Fig. 1. The basic network topology is composed of neurons. After the information is input by neurons, it is processed according to certain learning rules. The calculation results are output by neurons [30].

The development of artificial neural network has begun since the 1940s. In 1943, McCulloch, an American psychologist, and Pitts, a mathematician, jointly proposed the mathematical model of neurons in the threshold element model (M-P model for short), which opened the door to the research field of ANN, and the research on the information processing mode of neurons was also developing rapidly. In 1958, Rosenblatt et al. applied neural network to pattern recognition and developed a perceptual model named Mark I [31]. This kind of neural network has the ability of learning and self-organization, which also leads to the upsurge of neural network research. In 1969, Minsky and Papert found that the single-layer network structure was simple and could not solve linear inseparable problems such as XOR problems. The feasibility of multilayer network exists doubts [32].

This conclusion has seriously undermined the research on artificial neural networks.

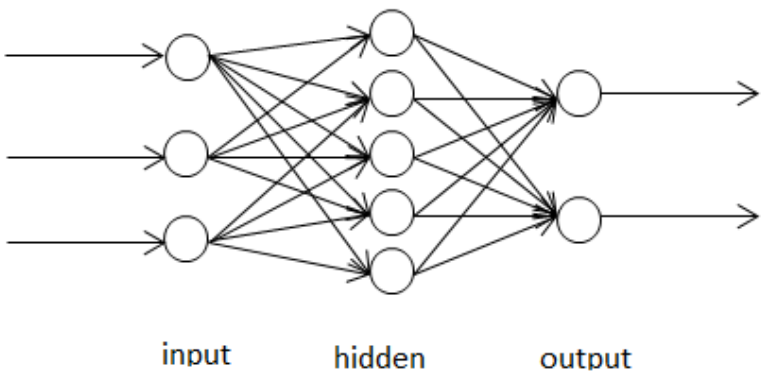

Fig. 1. Typical artificial neural network structure

In 1974, Werbos proposed the principle and algorithm of back propagation, providing a feasible way for the training of multi-layer neural networks [33]. The 1980s became a turning point in the development of neural networks. By 1982, physicist HOPFIELD John established Hopfield neural network model [34], This model has the characteristics of associative memory and optimization calculation, which may be used to solve complex problems and greatly promote the development of neural networks. In 1986, Werbos et al. analyzed and optimized the multi-layer back propagation algorithm, and solved Minsky ' s linear inseparable problem and the difficulty of manually setting parameters [35]. Back Propagation Algorithms for Multilayer Forward Neural Networks at the same time are rediscovered by RUMELHAART and Mc CELLAND [36]. With the development of computer hardware and neural network theory, in 2006, HINTON and SALAKHUTDINOV published a paper on “ 《Science》 ”. They first proposed the concept of “ deep learning ” and deepened the hidden layer of the network to seven layers [37]. Alex et al. designed eight layers of convolutional neural networks in 2012 [38], So the research of neural network is pushed to deep learning, which leads to the development of deep learning in research and application fields [39]. The theory of deep learning and deep neural network algorithm have developed rapidly in recent years, and a large number of scholars have invested in research in related fields.

2.1 Functional Features and Classification

Artificial neural network has the characteristics of parallel processing, distributed storage, good robustness, strong adaptability, adaptive and self-learning, and the functional characteristics of nonlinear mapping, associative memory, recognition and classification, associative memory [40]. These functions are well adapted to the needs of high-latitude, nonlinear process industries.

ANN can be divided into continuous and discrete type by function, feed-forward network and feedback network by topology structure, supervised learning network and unsupervised learning network by learning rules. Researchers have built various neural network models using different algorithms. Common back propagation neural network, radial basis function neural network, adaptive network, convolutional neural network, etc. [41]. All kinds of neural networks have their advantages and disadvantages, such as back propagation algorithm has strong nonlinear mapping and associative memory ability, and it is widely used in pattern recognition and fault diagnosis. However, there are some problems such as slow convergence speed and local optimal solution may appear when the parameters are improper. RBF neural network has fast convergence speed and good classification ability, but the algorithm needs to be improved [41].

The application of artificial neural network in chemical process is quite extensive and deepening. It is mainly used in fault diagnosis, process control and optimization, physical property estimation and expert system, quality control, quantitative structure-activity/ property correlation analysis, cluster analysis and other fields [42].

2.2 Application of ANN in Fault Diagnosis of Chemical Process

In the context of today 's large-scale integration of the chemical industry, some disturbances or failures in the process may be passed to the downstream process, resulting in unstable operation of the whole process and affecting the operation of the whole system [43]. Therefore, fault diagnosis plays a very important role in chemical production. Fault diagnosis requires the analysis of the data in the real-time process of chemical industry, the detection and analysis of the fault location, and the determination of the fault reason, location, time and mode, which prompts the operator to carry out the process recovery and ensures that the production process is in a safe working state [44]. The faults in the chemical process have the characteristics of coupling, continuity, time delay and uncertainty. In view of the problems existing in the traditional fault diagnosis methods of chemical process, such as low efficiency of fault feature extraction, low accuracy of fault diagnosis, unable to automatically extract fault features, and difficult to deal with massive process operation data, the neural network for fault diagnosis does not need accurate mechanism model and expert knowledge base, and only needs to establish a mathematical model with better prediction ability. The trained fault detection and diagnosis model is used for fault detection and identification, so it has advantages. BP and RBF ANN are widely used in fault diagnosis [45].

A chemical fault detection method based on sparse filter feature learning (SFFL) was developed by South China University of Technology [46]. This method adopts an unsupervised feature learning algorithm in deep learning network, namely sparse filtering feature learning algorithm. The algorithm, proposed by Ngiam and Andrew et al. 2011, can accurately extract features from raw data by optimizing the sparse distribution of learned features [47]. Sparse filtering algorithm has the advantages of adaptive learning, deep mining and more effective for nonlinear extraction.

The idea of this method is to train the preprocessed data by unsupervised training of sparse filtering model, so as to obtain the learned features, and then train the logistic regression classifier in a supervised way, and classify the learned features, so as to realize the fault detection of chemical process.

The pretreatment process is as follows. Firstly, the original data of chemical process collected by DCS or simulation system are standardized to eliminate the dimensional relationship between variables and accelerate the convergence of weight parameters. Then whitening pretreatment is carried out to reduce the redundancy of input samples, and the training sample set X is obtained after processing. Three-layer neural network is used to train SF model to obtain more accurate features. Principle as Fig. 2. The sample set X is input into the above SF model, and the weight matrix W1 and the initial learning feature f1 are obtained by optimizing the cost function. Then, the feature f1 is regarded as the input repeated training process of the model, and the weight matrix W2 and the final learning feature f2 are obtained. The logical regression model is set at the last layer of the neural network to classify f2 [47].

Researchers evaluated the fault detection performance of Tennessee Eastman process evaluation method. Tennessee Eastman Process, referred to as TE Process, was first proposed by Downs and Vogel in 1993 [48], and it mainly includes five operating units : reactor, condenser, vapor-liquid separator, stripper and circulating compressor. It is a computer simulation program for the actual chemical process of Isman Chemicals, Tennessee, USA. The simulated data are nonlinear, time-varying and strongly coupled. After revision [49], which was mainly used to evaluate the performance of process control and process monitoring methods, it has developed into a benchmark chemical process for FDD. The revised TE process comprises 28 faults. Two indicators are mainly used to evaluate the performance of the algorithm : fault detection rate FDR and false alarm rate FAR. The specific calculation formula is as follows :

$$FDR = \frac{F_1}{F} \times 100\% \quad (1)$$

$$FAR = \frac{N_1}{N} \times 100\% \quad (2)$$

In the formula, F is the total number of fault samples, and F_1 is the total number of fault samples detected by the method. N is the total number of normal samples, N_1 is the total number of samples whose normal samples are misstated as faults.

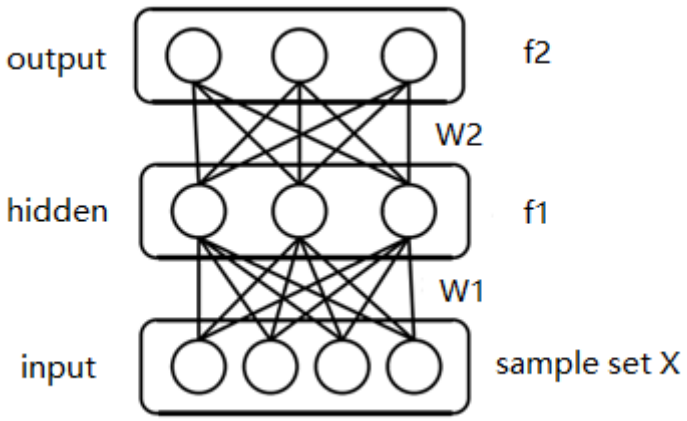

Fig. 2. Three-layer neural network structure of sparse filtering model [47]

The adjustable parameter of the algorithm is the number of features L, and researchers choose L = 200 as the number of features for learning. Under this feature number, the average fault detection rate of the test sample is 72.10 %, the average false alarm rate is 4.77 %, and the standard deviation is 0.38 %, which achieves good fault detection effect. In recent years, the application of deep convolutional neural network in chemical process fault diagnosis has been paid more and more attention. Convolutional neural network has strong ability to extract local unique features from data samples, and has good application prospects in chemical process fault diagnosis. It is expected to solve difficult problems such as large scale and strong nonlinearity of monitoring data in chemical production process.

Su [44] proposed a new method for fault diagnosis of chemical process based on convolution neural network, and took TE chemical process as an experimental case to test the model effect. The process of the method is as follows. Firstly, the original data of TE process are denoised by wavelet transform, and then the data are standardized preprocessed. Then, the convolutional neural network is used to supervise and learn the preprocessed data. The trained model adaptively extracts and learns the features from the TE process data, and then classifies the learned features. The fault classification results are output by the output layer soft max classifier. The experimental results show that the average fault detection rate reaches 80.31 %, and the false alarm rate of the test set is 2.837 %. It can be seen that the fault diagnosis method based on convolutional neural network can complete the fault diagnosis of TE process, and the effectiveness of the proposed method is verified.

Wu [50] proposed a fault diagnosis model for chemical process based on deep convolutional neural network. They used the two-dimensional characteristics of CNN data structure to process chemical data with time series, and applied it to the TE process. The algorithm training framework can be seen in Figure 3 50. The fault diagnosis program includes two stages: offline and online. The results show that the proposed DCNN-based fault diagnosis method has excellent performance in TE process benchmark mode, and the average FDR of 20 fault types reaches 88.2%. This shows that the fault diagnosis method based on CNN can still show good diagnostic performance in less training times [51].

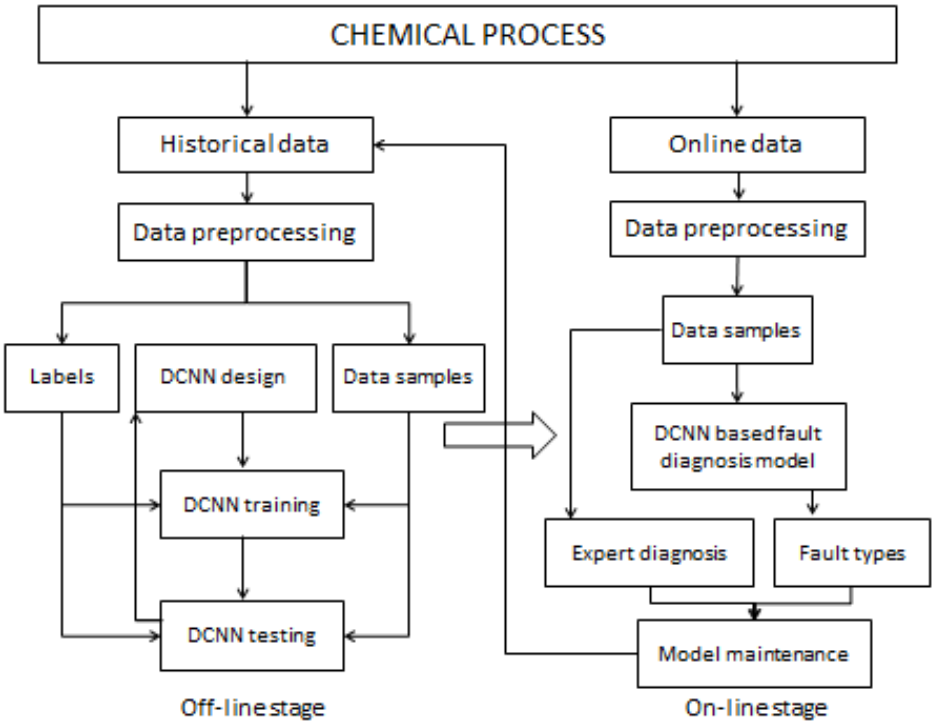

Fig. 3. The framework of the DCNN based fault diagnosis method [51]

Xia [39] proposed a fault diagnosis method for chemical process based on DRN model. The deep residual network model is a deep learning model based on the traditional convolutional neural network proposed by Chen et al.. The problem of deep neural network training is solved by using the fast connection of identity mapping. The new modified linear unit activation function and batch normalization method are used in the network, which can alleviate the problem of gradient disappearance or explosion [52]. Firstly, a whole process framework of fault diagnosis is set up. The whole process is divided into offline stage and online stage. The DRN model is trained by offline data, and the online data is input into the model to obtain the diagnosis results. Then the TE data is analyzed and processed, and the variables closely related to the process operation state are selected from all process variables. The correlation between various faults and normal conditions is analyzed by calculating the mutual information between normal data and fault data. The z-score normalization method is used to process the data, and the dimension transformation of the data is carried out. Then, a DRN diagnosis model is proposed and applied to TE process. The model achieves 93.3 % average FDR and 0.32 % average FPR for 20 kinds of faults, showing superior diagnostic performance. After the improvement of residual block, this model achieves 94.4 % average FDR and 0.28 % average FPR for 20 kinds of faults, and the training time of the model is greatly shortened, showing more superior diagnostic performance.

3. CONCLUSION AND OUTLOOK

Fault detection and diagnosis are hot topics in process system engineering research. After years of development, artificial neural network has been widely used in chemical process fault diagnosis, and is still developing rapidly. ANN has become an indispensable tool in chemical process, plays an irreplaceable role, saves a lot of manpower and material resources, and can get more perfect results. The deep neural network has better performance in the face of chemical process data with high dimensions, strong nonlinearity, high imbalance, difficult labelling and obvious dynamic characteristics, which further promotes the research in this field. The application of deep neural network in chemical process fault diagnosis is far from perfect. In order to improve the fault diagnosis performance of the model, researchers should be still working in the following directions: (1) As a data-based fault diagnosis method, the neural network model needs a large number of process data for training. Too little fault data often causes non-convergence and it is difficult to find the optimal parameters. This requires us to constantly use new fault data to update the model, so as to continuously update the established fault detection model, avoid or reduce fault misstatement and omission, and make the model more accurate and intelligent; (2) Researchers sometimes only consider the occurrence of a single fault, and the actual chemical process is likely to have multiple faults at the same time. Therefore, how to diagnose compound faults in chemical process is a problem worthy of consideration in the future.

DISCLAIMER

The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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